A Review on
Sensor, Signal, and Information Processing Algorithms

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Abstract

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14. ABSTRACT
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A. Introduction

There are many elements in a sensing system that need to be optimized in order to achieve a fully-adaptive sensing system. Some of these elements include the design of: processing techniques for sensing waveforms; information inference approaches for sensor networks; resource adaptive computations for sensing algorithms; and optimal methodologies for dynamic sensor scheduling and waveform adaptation.

Distributed sensing systems have been made feasible for use in wireless sensor networks by the development of independent and self-contained sensor devices [1–6]. In these networks, each sensor provides information about its surroundings to the other sensors and the base station. The challenge is to develop distributed and collaborative methods that are optimized for the particular application and hardware platform. A wireless sensor network consists of spatially distributed sensors which are capable of monitoring physical phenomena. They are now used in many areas, including military and healthcare applications, habitat monitoring, traffic control and space exploration [1, 3]. With recent advances in hardware technology, it has been possible to deploy a large number of devices that are able to sense, communicate, and also actuate. Sensors typically have limited processing and communication capability due to limited battery power. However, the fusion center of a wireless sensor network has fewer limitations in terms of processing and communication power.

The fusion center of a wireless sensor network can receive transmissions from the sensors over wireless channels so as to combine the received signals and make inferences about the observed phenomena. Distributed wireless sensor networks require distributed inference in the form of hypothesis testing (detection) and estimation. Distributed inference in a sensor network has garnered significant interest in recent years [7–9]. The important tasks of detection and estimation in a sensor network can be performed with reduced communication bandwidth requirements, increased reliability and reduced cost. This is very different from the classical centralized sensor networks, where all the sensors are wired to the fusion center that performs all the signal processing. Since the fusion center in decentralized networks only receives condensed information from the sensors, they exhibit a loss in performance when compared to centralized systems. However, this performance loss can be minimized by optimally processing the sensor measurements locally. The objective is to develop computationally efficient algorithms for the sensors locally as well as at the

fusion center.

Modern sensor signal and information processing relies heavily on both intensive and efficient computation capabilities. Intensive computation requires the ability of obtaining fine and detailed information from sensor waveforms. For example, processing schemes used for analysis, filtering, detection, estimation and classification can require intensive computation. However, for real-time computation, these schemes need to be efficiently implementable. A few such modern signal processing algorithms include time-frequency representations (which are analysis transforms used to process waveforms with time-varying spectra [10–12]), and filtering techniques like particle filtering (which are used to estimate dynamic state information from noisy data [13, 14]). Recent advances in integrated circuits enable us to exploit the development of both intensive and computationally efficient devices using multiple-core processors; these are extensively required in diverse fields, including communications [15–17], multimedia processing [18], radar [19–21], sonar, structural health monitoring, and biomedical engineering.

Agile sensing, defined as the adaptation of sensing strategies according to time-varying sensing environments and different sensing objectives, is essential in the design of sensing systems to achieve robust sensing and optimized performance. We specifically address two agile sensing applications: waveform-agile sensing techniques for radar [22–28] and multiple-input, multiple-output (MIMO) radar sensing [29–37], and parameter selectivity for underwater acoustic matched field tracking [38]. Specifically, waveform-agile sensing is important when performance improvements can be achieved when the transmitted waveform is dynamically designed or selected to match the sensing objective and the environment.

The rest of the paper is organized as follows. In Section B, we discuss wireless sensor network systems and address their practical issues, and we also review several real-time wireless sensor network applications. In Section C, distributed inference methodologies are presented for detection and estimation at the fusion center. We discuss the parallelized implementation steps of different algorithms on multi-core processor platforms, we introduce modifications of stochastic estimation algorithms to minimize the platform's communication overhead, and we discuss the effect of these modifications to estimation accuracy in Section D. Finally, in Section E, we discuss recent advances in waveform-agile sensing techniques used for radar and underwater matched field processing applications.
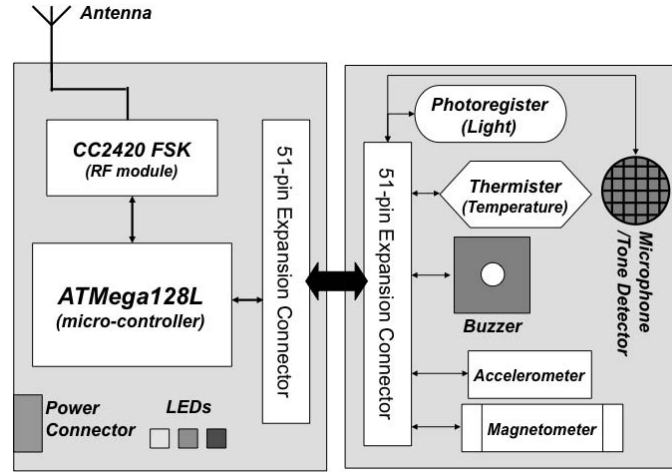
Figure 1: General architecture of a sensor node.

B. Wireless Sensor Networks

Wireless sensor networks consist of spatially distributed sensor nodes that are capable of monitoring physical phenomena and a base station, often called a fusion center. Each sensing node collects information about its surroundings and transmits the information to its neighboring nodes and the base station, where computationally intensive data processing tasks are performed. In this framework, the sensor nodes can be used for data acquisition, data forwarding and information processing. A generally-accepted architecture of an individual sensor node is shown in Figure 1. The three main components of such a sensing node are the sensor, the microcontroller, and the transceiver. The sensor consists of a transducer that converts the physical data to an electrical signal. It then feeds the acquired data to the microcontroller. The microcontroller is responsible for processing the acquired sensing data and controlling the wireless communication system. The transceiver allows data communication with other nodes in the network or with the base station. The network radio transmission is achieved using a media access control (MAC) protocol. Common to all three components is the power allocation unit that decides the power allocation scheme for the three components.

B.1. Development of Prototype Sensor Nodes

During the past several years, a few prototype sensor nodes were designed, including the Motes and PicoRadio [39] at the University of California, Berkeley, the uAMPS at MIT [40], and the
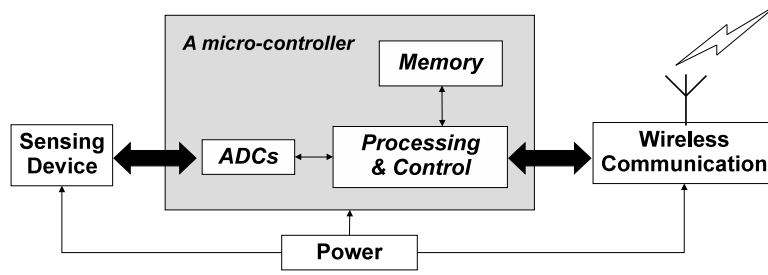
Figure 2: MICAz platform with MTS310CA sensor board.

GNOMES at Rice University [41]. In Europe, the Smart-Its project [42] was developed as a collaborative work between Lancaster University (United Kingdom), ETH Zurich (Switzerland), the University of Karlsruhe (Germany), the Interactive Institute (Sweden), and VTT Electronics (Finland). Using the Motes, several different types of wireless sensor network frameworks were developed for various application areas such as environmental monitoring, vital signs monitoring, and military applications [43]. Habitat monitoring was implemented using wireless sensor networks at Intel, the University of California, Berkeley [44], and the University of California, Los Angeles [45]. Autonomous sensor system, Wisden [46], was developed at the University of Southern California for monitoring the integrity of buildings. Wireless sensor networks were also applied to medical care. Vital Dust at Harvard University [47] was developed for emergency medical care and TinyOS-based wireless neural interfaces were designed at the University of California, Los Angeles [48]. A body sensor network was proposed using the Mote platform and discussed in [49]. For target tracking and localization, Cricket at MIT was developed using a unique hardware platform [50]. Shooter localization was demonstrated at Vanderbilt University with a high-performance sensor board devised for military applications [51]. For applications such as acoustic scene characterization, the Mote system interfaced with a DSP board was developed at the Sensor Signal and Information Processing (SenSIP) Center at Arizona State University [52].

B.2. Practical Issues of Wireless Sensor Networks

Sensors are associated with a number of resource constraints such as limited battery life, narrow bandwidth, small memory, drifting sampling rates, and insufficient throughput [53]. In particular, the limited bandwidth and low volume of data memory can be problematic for applications involving wideband, time-varying signals because of the higher sampling rate required. On the

other hand, radio communication modules draw more current than other modules. In a typical sensor setting, the microcontroller draws 8 mA in active mode, the radio frequency (RF) transceiver draws 19.7 mA in receiving mode and 17.4 mA in transmit mode [53]. The RF transceiver supports data rates upto 250 kbps. In order to avoid data collisions between multiple nodes in simultaneous operation, the data rates must be appropriately divided for use at each sensor node.

In addition to these implementation issues, several theoretical aspects of a distributed sensing framework present challenges [54]. If the sensors have no prior knowledge of the underlying signal being observed, then the ideal situation would be to gather the data from all sensors and analyze it at a central station. However, this process is associated with a high transmission cost [55]. A less costly scenario is one in which each sensor makes a decision based upon some a local decision rule and only transmits individual decisions. This fusion rule assumes that the actual decision rules are known at the base station for each sensor. This may be unreasonable in scenarios where signal characteristics are constantly changing. Hence, a collaborative sensing scheme can be valuable when local information captured at the node level is analyzed or intelligently combined later with information from other local sensor nodes to improve system performance. The following section reviews application specific sensing platforms and their collaborative sensing frameworks for use in real-time wireless sensor networks.

B.3. Real-Time Wireless Sensor Networks

B.3.1. Structural Health Monitoring

A wireless sensor network system was designed in [46] for structural-response data acquisition. In the paper, the Wisden used a 20 kHz vibration card, with four channels and 16-bit ADCs and an accelerometer, whose tri-axis ranged from -2.5 g to 2.5 g, to diagnose structural damage and integrity. Due to the limited bandwidth of the RF transceiver in the mote, each node compressed the acquired data using threshold-based event detection and wavelet decomposition techniques. To achieve reliable data transport, each node stored the compressed data on an EEPROM and transmitted it to a base station using a specific protocol scheme [56]. Note that the latest version of Wisden integrates onset detection and lossy compression so as to allow users to detect a vibration event while decreasing the amount of irrelevant noise data. In [57], the sampling rate limits of the Wisden system were characterized, and the limits due to transmission rate and the EEPROM access latency were identified as two main weaknesses of the system.

B.3.2. Acoustic Node Localization

Geographic node localization for wireless sensor networks were reported in [58] using an acoustic ranging method. In this network, one node acting as a beacon first gave notice to other nodes using RF messaging, and then it emitted an identical series of acoustic chirps using a buzzer on the sensor board. As this chirp signal was predefined and known to the other nodes located away from the beacon node, they can sense each chirp, with certain intervals from the emission times, using the microphone on the sensor board. Here, sensors in the other nodes acquired the chirps in order and then added them together as a single chirp signal. The resulting chirp signal was filtered using a 35-tap finite impulse response (FIR) filter with integer coefficients, whose lower and upper frequency bounds were 4 kHz and 4.5 kHz, respectively. The filtered output had a local peak in the interval where each chirp was placed. The experiment was performed deploying 50 Motes in a 1,530 m area without obstructions, where the speed of sound was 340 m/s at 35°C and 60% humidity. It was shown that the error in the estimates increased linearly with the actual distance, and the maximum error of the range estimate was about 20 cm.

B.3.3. Shooter Localization

Shooter localization techniques were designed and implemented using wireless sensor networks in [51, 59]. In this application, the activated nodes among the deployed nodes detected the muzzle blast, measured the time-of-arrival (TOA), and sent the measured results to a base station where the location of the shooter was estimated. For this application, two types of acoustic sensor boards were designed to measure the TOA. On the first sensor board, an FPGA computed the angle-of-arrival using three microphones, and the resulting detection range was 30 m. Due to the limited size of the FPGA component, the algorithm used was not very flexible. On the second sensor board, a DSP board was thus used instead of an FPGA. The detection range was extended to 150 m. An experiment was performed deploying 60 sensors in a 100×50 meter area, with a 5 m node spacing distance and 40 shots. The average shooter detection error was 0.52 m with two-dimensional mapping and 0.87 m for three-dimensional mapping.

B.3.4. Image Sensing

An address-event image sensor was developed using wireless sensor networks in [60]. The address-event representation introduced optimized data extraction of specific information such as

light saturation, motion and contours at the sensor level. Each pixel of the address-event representation sensing allowed an event to be signaled when it satisfied a certain threshold voltage. These events could be rank-encoded to accomplish low-complexity signal processing algorithms with low-power consumption. This imaging scheme significantly reduced the redundancy of full image data. It was implemented on three different platforms, and the captured images were used to recognize a few characters and six American sign language signs at the node-level.

B.3.5. Acoustic Scene Characterization

The acoustic scene monitoring problem using wireless sensor networks was considered in [61–63]. The work explored the development and characterization of a low-complexity voice activity detection algorithm, the efficient implementation of a gender classification algorithm, and the development of iterative data fusion algorithms that minimize classification errors. The Crossbow sensing platforms were employed to detect voice activity and to classify gender.
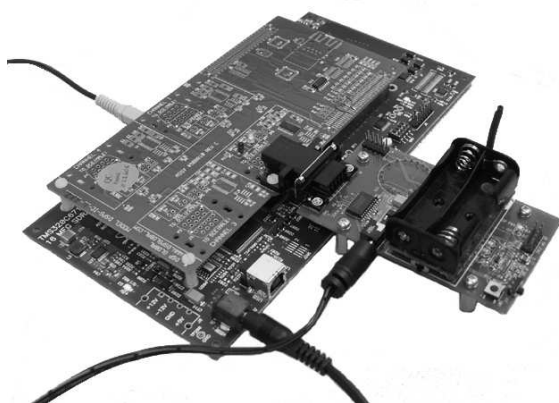

Figure 3: TMS320C6713 DSK interfaced with the MICAz[TM] platform using the RS232 connection.

In order to overcome the bandwidth and throughput constraints, a DSP board [64] was attached to each Mote to enhance its computational capabilities in [52]. As a result, most of the signal processing routines were carried out on the DSP board, while the Mote was responsible for transmitting the acquired data to the base station and to other Motes. Figure 3 shows the platform where the DSP board was interfaced with the Mote platform through an RS232 connection. The floating-point output-data from the DSP board was formatted with the IEEE standard 754 [65] and then encoded for transmission. The constructed packet was transmitted from the DSP board to
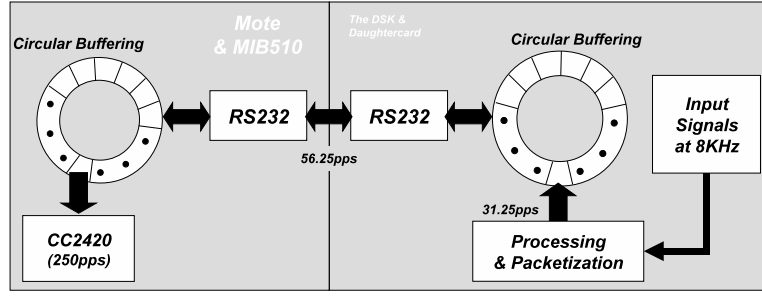
Figure 4: Data flow between a mote and the TI DSP board.

the Mote through the RS232 connection at 57,600 bits per second (bps) data rate, set by TinyOS, and was then transmitted to the base station through a wireless channel. A single packet can be extended up to 128 bytes and was designed to contain all extracted acoustic features from a single frame (256 samples). Hence, the packets were required to run at 31.25 packets per second in this sensing platform. For data communication between the Mote and the DSP board, two circular buffers were programmed, as shown in Figure 4. Therefore, acoustic features were extracted from the audio signal at each sensor on a frame by frame basis, and only these features were transmitted to the base station. The acoustic scene analysis was then performed at the base station using only the transmitted features.

The acoustic scene involved the following sensing tasks: speech discrimination, and voice monitoring and recognition of the number of speakers, their gender and emotional state. Each sensor performed all of these tasks, where local acoustic scenes were measured. These measurements were transmitted to the base station, where acoustic scenes were characterized in a hierarchical and selective manner. The speech discrimination algorithm was based on time-domain and frequency-domain acoustic features that included frame energy, normalized energy, band-energy ratio, and tonality [66]. The number of speakers in the speech signals was determined by analyzing the modulation characteristics of the signals in a quantitative fashion [66]. The modulation spectrum was calculated by analyzing the intensity envelope of the signals in the frequency domain [67]. The gender and emotional state analysis were performed using acoustic features (pitch and RASTA-PLP [66]). These features were extracted at the sensor and transmitted to the base station, where a pre-trained classifier was used to classify them. The parameters extracted for voice monitoring were associated low-complexity vocoders such as LPC-10 and full-rate GSM [68].

C. Distributed Inference Sensing

With recent advances in hardware technology, it has been possible to deploy a large number of devices that are capable to sense, communicate, and infer information about physical phenomena that they observe. Distributed inference in a sensor network has attracted a lot of interest in recent years [7–9]. Traditionally, distributed detection algorithms focus on perfect but bandwidth-constrained communication channels. The focus is mainly on issues such as conditional independence [69, 70] versus correlated sensor measurements at the sensing stage [71–74]. The bandwidth-constraint problem is often formulated in the form of calculating the number of bits per sensor and finding the optimal bit allocation amongst sensors given the total number of bits that can be transmitted by the sensor to the fusion center under the assumption of lossless communication [2, 75–81]. Fusion algorithms for such cases have also been studied in [82–84].

More recently, channel-aware signal processing algorithms that account for non-ideal transmission channels, assuming perfect channel information both at the sensors and the fusion center, were studied in [85–87]. In [88], by relaxing the lossless communication assumption, fusion algorithms combined local decisions that were corrupted during the transmission process due to channel fading. Also, a new likelihood ratio based test was proposed that did not require instantaneous channel state information but only used channel fading statistics. In [89], local decision fusion rules were considered when the fusion center acquired varying degrees of channel information and found the optimal local decision rules that minimized the probability of error. Note that most literature focused on binary hypothesis distributed detection.

Although most applications on sensor networks require information on the observed state, a source parameter can also be considered that can be obtained using distributed estimation in sensor networks [90, 91], tracking [92], data fusion [93, 94] and distributed control [95–98]. Distributed estimation can be performed at the fusion center using (quantized) measurements from the sensors or it can be performed at the sensor nodes themselves using the measurements shared by other sensor nodes (ad-hoc sensor network). Universal decentralized estimators of a source observed in additive noise without any knowledge of the noise distribution were considered in [99, 100]. Other works that assumed either the structure or knowledge of the parameters of the noise distribution were considered in [101–103]. Most of the existing literature focused on finite-rate transmissions of quantized sensor observations [104–109], delivered to the fusion center by analog or digital
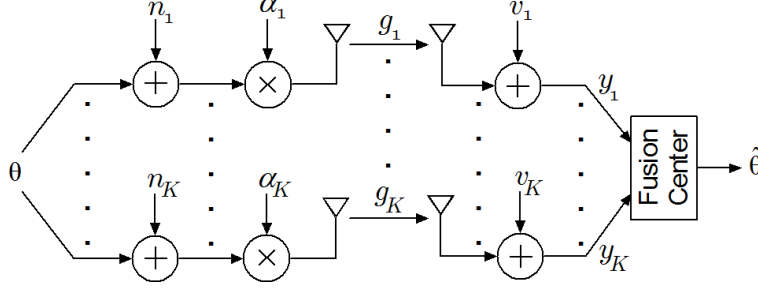
Figure 5: Wireless sensor network using K sensors and an orthogonal fading channel model to estimate a random parameter source θ at the fusion center.

transmission methods. One analog transmission method is the amplify-and-forward method. In digital transmission, observations are quantized, encoded, and transmitted using digital modulation.

The channels between the sensors and the fusion center can be orthogonal so that the fusion center has access to individual transmissions from the sensors. The channels can also be multiple-access, where the fusion center only has access to the sum of the signals from all the sensors. These channels are discussed next in more detail.

C.1. Orthogonal Channels and Sensor Networks

Figure 5 demonstrates a wireless sensor network based on a widely-adopted distributed inference model using an orthogonal fading channel. Based on the application, the orthogonality can be obtained using a multiple-access scheme such as frequency-division multiple-access (FDMA), code-division multiple-access (CDMA), or time-division multiple-access (TDMA). The fusion center receives K non-interfering signals, transmitted by K sensors, each of which has information on an unknown random source θ with zero-mean and variance σ_θ^2. At the kth sensor, the source is corrupted by zero-mean, additive, complex Gaussian noise n_k with variance $\sigma_{n_k}^2$. Using a simple amplify-forward analog transmission scheme, the kth sensor amplifies its incoming analog signal by a factor α_k before transmitting it on the kth flat fading orthogonal channel to the fusion center. The channel is assumed to be Rayleigh flat fading with gain g_k, and it also has additive, zero-mean, white Gaussian noise with variance $\sigma_{v_k}^2$. The amplification factor α_k may or may not depend on the fading coefficient g_k, depending on whether the channel state information (CSI) is available at the sensor. Using the combining rule that maximizes the signal-to-noise ratio (SNR) at the fusion
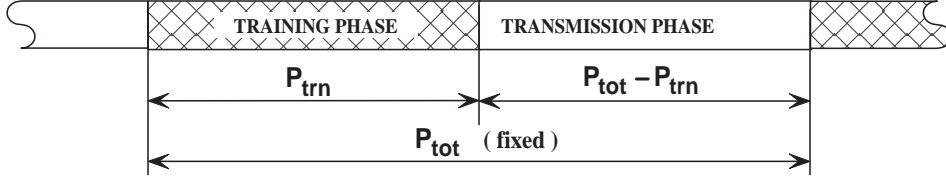
Figure 6: Training and data transmission phases. P_{trn} is the power during training and $P_{\text{tot}}=P_{\text{total}}$ is the total power.

center, and defining P_{total} as the total transmit power by all the sensors, then the SNR at the output of the fusion center is given by

$$\text{SNR} = \sum_{k=1}^{K} \eta_k \, \gamma_k \Big/ \left(\eta_k + K \left(\gamma_k \, \sigma_\theta^2 + 1 \right) / P_{\text{total}} \right) , \qquad (1)$$

where $\gamma_k = 1/\sigma_{n_k}^2$ is the sensing SNR of the kth channel and $\eta_k = |g_k|^2/\sigma_{v_k}^2$ is the instantaneous gain of the kth channel. Note that the SNR in (1) is random as it depends on the random parameter η_k. The variance of the best linear unbiased estimator (BLUE) of θ was derived to be 1/SNR, and an estimation diversity order d was established for asymptotically large K and a fixed total power P_{total} as increasing the number of sensors improved the estimation performance [110].

For asymptotically large powers, when the sensing SNRs, $\gamma_k = \gamma$, $k = 1, \dots, K$, are all equal, then the diversity order d has a tight bound that is given by [111]

$$K - (z/\gamma) \ \leq d \ \leq \ K - \lfloor z/\gamma \rfloor ,$$

where z is the outage threshold. This means that the outage power scales as $P_{\text{out}} \approx 1/(P_{\text{total}}^d)$. If the transmission power of each sensor is fixed, the outage can be shown to go to zero as $P_{\text{out}} = \Pr[\text{SNR} < z] \approx e^{-K \log K}$ in the sense of exponential equivalence, i.e., $\ln(P_{\text{out}}) = O(K \log K)$.

The performance of the estimator in the absence of CSI at the sensors was considered in [110, 112]. Using a two-phase approach as in Figure 6, the fading coefficients were first estimated and then used to estimate the source θ [112]. It was shown that there is a tradeoff problem between the total power used for training the channel and the power used to transmit information. This optimization problem was solved, and it was found that exactly half of the total power should be used for training [112]. The power penalty ratio needed to obtain the same performance as the perfect CSI case can be arbitrarily large, but it approaches 6 dB when the total power is large. The 3 dB loss is due to training allocation and the remaining 3 dB is a loss in performance due to
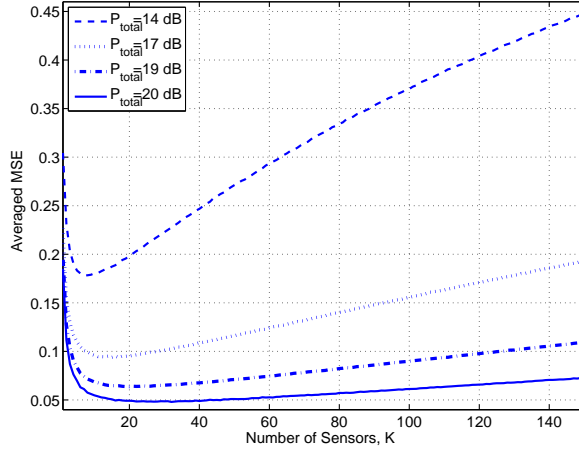
Figure 7: Averaged MSE for estimating the source at the fusion center for a varying number of sensors when the channel is unknown. Note that increasing the number of sensors eventually degrades the MSE.

the imperfect channel estimation. Unlike the perfect CSI case, for a fixed total power, increasing the number of sensors eventually degrades the estimation mean-squared error (MSE). The optimum number of sensors that minimizes the MSE was simulated for different values of total power P_{total}, and the results are demonstrated in Figure 7. As it can be observed from the figure, as the total power P_{total} increases, the number of sensors that minimizes the MSE increases. The results also indicated that increasing the number of sensors indefinitely does not yield better performance [112]. The benefits to be had in increasing the number of sensors are offset by the necessity to estimate their channels, which also consumes power. More generally, the issue of channel estimation cannot be abstracted from the issue of performance, and it motivates studying distributed inference in a way that incorporates the physical layer communication architecture.

C.2. Multiple-access Channels and Sensor Networks

Figure 8 demonstrates the multiple-access channel model, where the fusion center has access only to the sum of faded and noisy signals transmitted over K independent sensors, each with an amplification factor α_k, $k = 1, \ldots, K$. Note that detailed information on the optimality of the amplify-and-forward transmission for a wireless sensor network with a Gaussian source and Gaussian coherent MAC and a large number of sensors can be found in [110, 113–118]. Acquiring channel information at each of the K sensors in the multiple-access channel model in the network
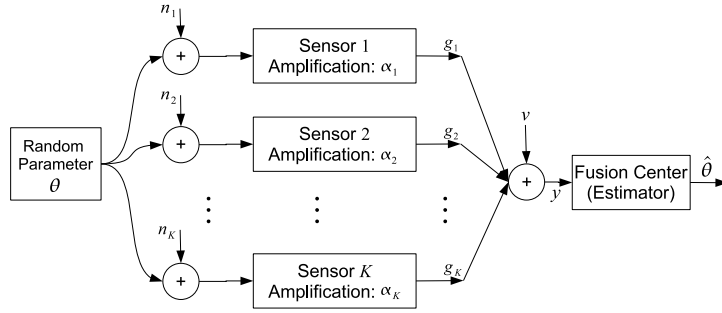
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Figure 8: Wireless sensor network using K sensors and a multiple-access fading channel model used to estimate a random parameter source θ at the fusion center.

can be quite costly. However, it is possible to do distributed estimation without channel knowledge at each sensor if the fading channel coefficients are not zero-mean [118–120]. As this is often not the case or the phase differences in the channel means add destructively, it is absolutely necessary for some (or at least partial) channel information to be available at the sensor for this additive multiple-access channel scenario. This is demonstrated next.

Considering the unknown channel case with $\alpha_k = \sqrt{P_{\text{total}}/K}$, the variance of the BLUE estimator of θ from the observation snapshot y can be shown to be a function of the channel coefficients $g_k, k = 1, \ldots, K$. Specifically, assuming that at each sensor, the source is corrupted by zero-mean, additive, complex Gaussian noise with the same variance σ_n^2 and that the channel for each sensor has additive, zero-mean white Gaussian noise with the same variance σ_v^2, then the conditional variance of the source estimator is given by

$$\text{var}\left(\hat{\theta} \mid g_1, g_2, \ldots, g_K\right) = \frac{1}{K} \frac{(\sigma_n^2 \, P_{\text{total}} \, /K) \, \sum_{k=1}^{K} |g_k|^2 + \sigma_v^2}{P_{\text{total}} \left| \frac{1}{K} \sum_{k=1}^{K} g_k \right|^2} . \tag{2}$$

This conditional variance is random as it depends on the random channel coefficients. It can be shown that its distribution has a heavy tail in the sense that its expected value cannot be computed. From a practical view point, this means that realizations of the conditional variance, over distributions of the fading channel coefficients, have a very large dynamic range. This is very undesirable as the conditional variance can be high with high probability. This shows that there is a fundamental bottleneck in distributed estimation problems over multiple-access fading channels because the sensor-transmitted signals can add destructively due to the zero-mean nature of the

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fading. Therefore, it is absolutely necessary to have some channel information available at the sensor during transmission.

In [110], an amplify-and-forward approach was used with an orthogonal multiple-access channel and perfect channel knowledge at the sensor. The conditional variance for two cases, the impractical full-CSI case and the more practical partial-CSI case, were studied in [120–122] in order to understand how the channel should be quantized as the number of sensors increased. Specifically, it was found that

$$\lim_{K \to \infty} K \operatorname{var}\left(\hat{\theta} \mid g_1, g_2, \ldots, g_K\right) = C$$

which converges in probability to a deterministic constant C, depending on what CSI is available at the sensors and the channel distribution. This means that the variance decays according to $O(1/K)$, and the comparisons of the constant C for different schemes can be used to quantify the benefits of partial CSI on performance. In particular, it can be shown that $C_{\text{phase-only}} = (4/\pi) C_{\text{AWGN}}$. This means that when phase-only feedback is available, the asymptotic variance degrades no more than a factor of $4/\pi$ when compared with the ideal, non-fading additive white Gaussian noise (AWGN) case. It was also shown in [123–125] that, although the expected value of the conditional variance in Equation (2) does not exist for one receiver antenna, it can be computed for or two or more receiver antennas. This is a very interesting result that shows that there is not only a quantitative, but also a qualitative difference in exploiting multiple antennas at the fusion center. The conditional variance does not have a heavy tail when two or more antennas are present at the fusion center. This result can also be viewed as a more general indication that, with estimation, the benefits of multiple antennas are quite different than those seen in data transmission applications.

Recently, impulse-radio ultra-wide band (UWB) modulation was considered for wideband wireless sensor network applications due to its low-power and carrier-free architecture. Distributed detection with UWB modulation using practical power and fading and synchronization constraints over frequency-selective channels was considered in [126–128]. As the UWB signal experiences a frequency-selective channel and has an extremely narrow pulse duration, it is often not practical to feedback full CSI to all sensors or synchronize them at the pulse level at the receiver. The tradeoff between detection performance and feedback overhead, ways to achieve asymptotically optimal performance, and the effects of system bandwidth and power on asymptotical optimality were discussed in [129].

D. Resource-Agile Sensing and Processing

Modern sensor, signal, and information processing algorithms rely heavily on their computational cost as well as their performance level. Recent advances in integrated circuits enable the development of both intensive and efficient computational algorithms using multi-core processors. These are processing systems composed of two or more computers that aim to increase throughput without significantly increasing the power consumption with respect to a single processor. Examples of multi-core processors include the Intel Core 2 Duo, AMD Opteron, and Sun Niagra processor. In order to fully utilize the computational power of the multi-core processor architectures, the existing processing algorithms need to be adapted to the parallel computation environment. The amount of achievable improvement will depend on the extent by which an algorithm can be parallelized [130].

Several applications of parallelized advanced signal processing algorithms on multi-core processor systems will be discussed to demonstrate how to achieve resource-agile sensing and processing capabilities. The applications specifically discussed are time-frequency representation (TFR) algorithms and the particle filter sequential Monte Carlo algorithm. Resource-agile parallel implementation of these algorithms requires partitioning the computational load between multiple processors to minimize overhead, which may also require algorithmic modifications.

D.1. Multi-core Processor Implementation of Time-Frequency Representation Algorithms

A time-frequency representation (TFR), $T_x(t, f)$, is a two-dimensional (2-D) transformation that can adequately and jointly represent a signal $x(t)$ in both the time and frequency domain [10]. TFRs are useful in applications where the signals or systems involved have time-dependent properties that vary with frequency.

One example of a linear TFR is the short-time Fourier transform (STFT) that is defined as

$$S_x(t, f; h) = \int_{-\infty}^{\infty} x(\tau) \, h^*(\tau - t) \, e^{-j2\pi f\tau} \, d\tau$$

where $h(t)$ is a lowpass window of duration MT_s, M is the window length in discrete time, and T_s is the sampling period. For any given time, the signal is multiplied by a shifted version of the window, and the Fourier transform (FT) of the windowed signal is computed as the frequency spectrum at that particular time point. This is a very practical TFR as it is easy to compute; however, it can get very computational intensive for very large data sets.

Using a P-processor architecture, the STFT can be computed without any loss of accuracy. The processors can communicate with each other through a global shared bus. The pth processor, $p = 1, \ldots, P$, can also communicate with the $(p - 1)$th and $(p + 1)$th processors using inter-processor links. For N signal samples and M window samples, the data can be divided into P sets during a pre-processing stage. At each time t, the pth processor, $p = 1, \cdots, P$, can compute N/P consecutive STFT outputs whose index ranges from $(p-1)N/P$ to $[(pN/P) - 1]$. To compute these outputs, the pth processor requires signal samples that range from index $(p - 1)N/P$ to $[(pN/P) + (M - 2)]$. The extra $M - 1$ samples are sent to each processor so that it can complete its calculations without needing to request samples from its neighboring processor. Another option is for the pth processor to send its latest data samples to the $(p - 1)$th processor after each discrete FT is computed. While this takes only one cycle for an architecture with dedicated links, it takes P cycles for the shared bus architecture. However, if the computations in each processor are staggered, then the computations and the communication can be overlapped; in this case, the communication overhead can be negligible. Simulation results of this multi-core processor architecture can be found in [131].

The Wigner distribution (WD) is a quadratic TFR that does not use a window and preserves many signal properties [10]. It is defined as

$$\mathrm{WD}_x(t, f) = \int_{-\infty}^{\infty} x(t + \tau/2) \, x^*(t - \tau/2) \, e^{-j2\pi\tau f} \, d\tau \, .$$

A simple way to calculating the WD at a fixed time t is to first multiply the signal shifted by $\tau/2$ with the same signal but shifted by $-\tau/2$ and to then compute the FT of each row of the product matrix. The parallel implementation for obtaining the product matrix can be performed using P processors. The discrete signal with N samples is first divided into P sets. The pth processor has input data values indexed from $(p - 1)N/P$ to $(pN/P) - 1$ in register one (R1) and the conjugated values in register two (R2). In order to calculate the values for the time samples for the lth time-shift, the pth processor shifts $l/2$ data entries at the end of its R1 to the beginning of the R1 of the $(p + 1)$th processor. The pth processor shifts $l/2$ data entries at the beginning of its R2 to the end of the R2 of the $(p - 1)$th processor. The products of the corresponding values in R1 and R2 are then computed and stored as the elements of the product matrix. This step is repeated until both signals have been shifted by $N/2$. In this procedure, in each step, $2P$ data are reassigned to the different processors. While this requires only 2 cycles for a multi-core processor architecture with

dedicated interprocessor links, the overhead is a lot more for the shared bus architecture. After the product matrix is obtained, the computation of the FT is performed in parallel in each processor. Specifically, each processor computes N-point discrete FTs N/P times, which does not require any interprocessor communication [131].

D.2. Multi-core Processor Implementation of the Particle Filter Algorithm

Particle filtering is a sequential Monte-Carlo estimation technique that is used to solve nonlinear and/or non-Gaussian dynamic system estimation problems. It involves sequential estimation of the states of a dynamic system based on received noisy observations. Some example applications include target tracking, wireless communication channel estimation, and neural network training [14]. The general state space representation is characterized by a state equation and an observation equation. Specifically, the state equation describes the relationship between an unknown state parameter vector $\mathbf{x}_k$ at discrete time step k with its previous time step value as

$$\mathbf{x}_k = f_{k-1}(\mathbf{x}_{k-1}, \mathbf{v}_{k-1}). \tag{3}$$

Here, $f_{k-1}(\cdot, \cdot)$ is a known, possibly nonlinear function and $\mathbf{v}_{k-1}$ is a random process vector, possibly non-Gaussian, that represents possible state modeling uncertainty. The observation equation relates available information, such as a noisy measurement vector $\mathbf{z}_k$ at time k, with the state vector, and it is given by

$$\mathbf{z}_k = h_k(\mathbf{x}_k, \mathbf{w}_k), \tag{4}$$

where $h_k(\cdot, \cdot)$ is a known, possibly nonlinear function and $\mathbf{w}_k$ is the measurement noise vector that is possibly non-Gaussian. The filtering problem involves the estimation of the conditional probability density function $p(\mathbf{x}_k|\mathbf{Z}_k)$, where $\mathbf{Z}_k = \{\mathbf{z}_1, \mathbf{z}_2, \ldots, \mathbf{z}_k\}$. For nonlinear and/or non-Gaussian problems, the particle filtering technique approximates the posterior density $p(\mathbf{x}_k|\mathbf{Z}_k)$ by a set of N_p particles $\mathbf{x}_k^i$ and associated weights w_k^i, $i = 1, \ldots, N_p$, as $p(\mathbf{x}_k|\mathbf{Z}_k) \approx \sum_{i=1}^{N_p} w_k^i \delta(\mathbf{x}_k - \mathbf{x}_k^i)$ [14, 132]. Note that there are different forms of the particle filtering algorithm, based on the choice of the importance density [132]. The most commonly used algorithm is the sequential importance resampling particle filter (SIRPF) algorithm: it draws the particles from the transitional prior $p(\mathbf{x}_k|\mathbf{x}_k^i)$, and it approximates the importance weights as $w_k^i \propto w_{k-1}^i p(\mathbf{z}_k|\mathbf{x}_k^i)$ before normalizing them such that $\sum_i w_k^i = N_p$ and resampling the particles based on the normalized weights.
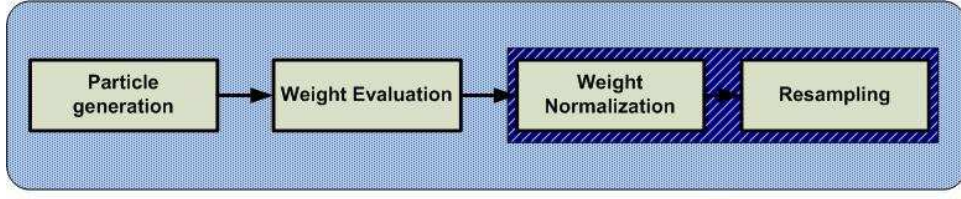
Figure 9: Block diagram showing the different stages of a particle filtering algorithm.

The four main steps in the particle filtering algorithm are: (i) particle generation; (ii) weight evaluation; (iii) normalization of the weights; and (iv) resampling. Some recent contributions for the parallel implementation of particle filters include a parameterized framework for field-programmable gate array (FPGA) implementation that reuses blocks [133], and algorithmic modifications to improve the speed of operation for the Gaussian particle filter [134] and for the Kullback-Leibler distance (KLD) sampling approach [135]. New methods of resampling [136] such as the residual-systematic resampling, partial resampling, and delayed resampling have also been introduced to overcome the hardware complexity in the resampling stage.

In [131], the particle filter was implemented on a multi-core processor platform using a control processor and several processors that communicated with each other through a common interprocessor bus. In order to implement the SIRPF on this multi-core processor platform, the processing of N_p particles were distributed among the P available processors. The distribution had to be such that N_p/P particles were processed by each processor at each time step. The operations of the SIRPF were divided into different stages, and each processor performed some of these stages concurrently and interacted with the central processor during other stages.

The particle filter algorithms can be straightforwardly and directly mapped into the multi-core processor platform, as demonstrated in Figure 9. The figure maps each step individually into processors; however, this approach involves significant and uncertain communication between the central processor and the other processors. In order to reduce the interprocessor communication, algorithm level modifications were introduced to avoid transmitting the information on all the particles and weights to the central processor [131]. Specifically, a reduced set of information was provided to the central processor which was used for resampling the particles. These modifications came at the cost of accuracy loss. The modified mapping scheme for parallel particle filter implementation is shown in Figure 11. The performance of the parallel particle filter implementation

is demonstrated using the scalar estimation problem discussed in [137], where a nonlinear state sequence x is estimated from noisy measurements. The state space representation is given by

$$x_k = 1 + \sin(\omega \pi (k-1)) + \phi_1 \, x_{k-1} + v_{k-1}, \tag{5}$$

$$z_k = \begin{cases} \phi_2 \, x_k^2 + w_k, & k \le 30 \\ \phi_3 \, x_k - 2 + w_k, & k > 30 \end{cases}, \tag{6}$$

where v_k and w_k are the process modeling error and measurement noise, respectively, and the scalar parameters were chosen to be $\omega = 4 \times 10^{-2}$, $\phi_1 = 0.5$, $\phi_2 = 0.2$, and $\phi_3 = 0.5$. The estimation for 60 time steps was conducted using the SIRPF algorithm with $N_p = 1,000$ particles. Three different platforms were considered with $P = 1, 4$ and 8 processors. The computation of the 1,000 particles was distributed equally among the P processors. Each algorithm iteration was averaged over 100 Monte Carlo simulations on an Intel dual-core Pentium-D 3 GHz system with 2 GB RAM. Figure 10 shows the overlaid performance plot for the x_k estimation for the three platform systems. The estimation performed using a single processor had very high accuracy; the averaged deviation from the true value was as low as 10^{-3}. For the 4-processor and 8-processor cases, the relative deviation was 5×10^{-2} and 11.1×10^{-2}, respectively. The processing time was reduced, as expected, for the multi-core processor systems. As the number of processors increased, the number of particles processed by each processor was reduced and so the processing time for each processor was also reduced. However, the amount of data transmitted to the central processor increased, thereby also increasing the communication time.

E. Waveform-Agile Sensing

Agile sensing algorithms enable sensor systems to adapt to changing environments or to varying sensing objectives by optimizing some performance measure. Recently, there has been a lot of interest on waveform-agile sensing, where the waveform is adaptively designed to dynamically improve the sensing performance [138, 139]. Some applications, where waveform-agile sensing was successfully applied, are described next.

E.1. Waveform-Agile Target Tracking in Radar

Measurements from active radar sensors are used to track moving targets. As the position and velocity of a target change, the target-sensor geometry and sensing environment also change, and
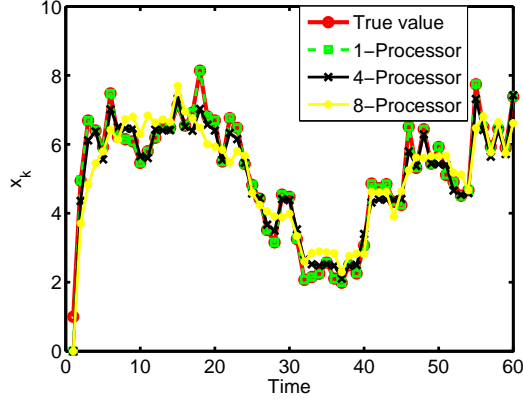
Figure 10: True and estimated value of the dynamic scalar parameter x_k in Equation (5) for different number of multi-core processors.

so does the range and range-rate sensor measurement information. One possible method to adapt the measurement characteristics is to appropriately select the transmitted waveform configuration in order to optimize the tracking performance. Specifically, dynamic waveform adaptation, as depicted in Figure 12, is an agile-sensing methodology that designs the transmitted waveform at the next time step such that the tracker's performance requirements are optimally met. Another important consideration in designing the transmit waveform is computational sensing constraints. As the number of sensors used as well as the sensor capabilities increase, the amount of information the sensors collect also increases, resulting in large processing requirements. One possible way to lower data rates while increasing tracking performance is to combine waveform agile sensing with sensor scheduling.

Waveform-agile sensing methodologies have been based either on information theory or control theory approaches. The information theoretic approach method designs radar waveforms by maximizing the mutual information between targets and waveform-dependent observations in [140–143]. In [144], sensor scheduling actions were based on the expected information, while in [145, 146], a wavelet decomposition was used to design waveforms to increase the extraction of target information in non-stationary environments. Although the control theoretic approach was initially focused on the selection of waveforms to satisfy constraints on the desired peak or average power of the transmitted waveform [147, 148], more recently, methodologies were developed to optimize a cost function, such as the mean-squared tracking estimation error, by appropriately
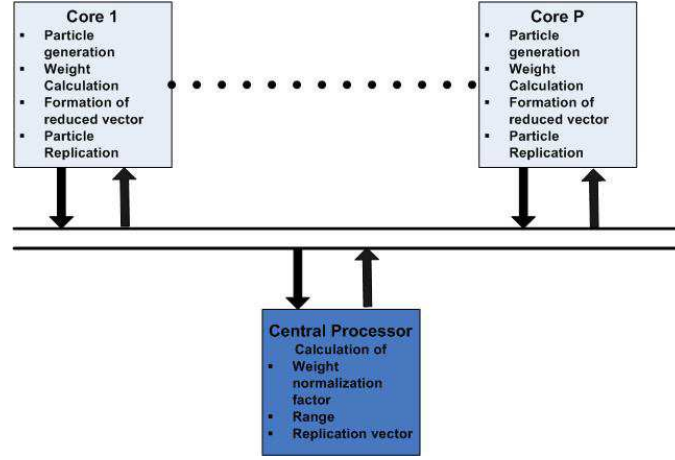
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Figure 11: Functional block diagram of the multi-core processor implementation of the particle filtering algorithm.
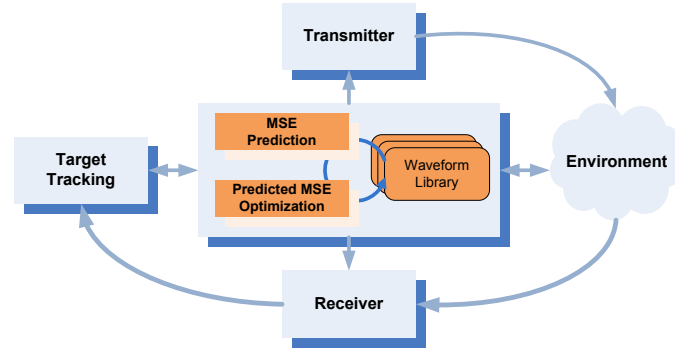

Figure 12: Illustration of waveform-agile sensing for target tracking.

selecting the transmit waveform for the next time step [22–28]. This optimization results in a feedback loop since the waveform selected affects the next observation and hence the tracker update, which then directs the next waveform choice.

A critical component in the formulation of selecting a waveform to optimize a cost function at the next time step is a mechanism to predict the expected observation errors from a particular waveform choice. When minimizing the tracking mean-squared error (MSE), the Cramér-Rao lower bound (CRLB) characterization is widely used to approximate the predicted error covariance under the assumption of high SNR. This is because the CRLB can be obtained directly from the curvature of the peak of the ambiguity function (AF) at the origin in the delay-Doppler plane [22, 25], and the AF provides a measure of the estimation accuracy of the delay and Doppler of

the target [149–151]. Using the high SNR assumption, the CRLB agile sensing approach was applied to different radar scenes including narrowband and wideband scenarios and environments with clutter and multiple targets [24, 25, 152]. Since the CRLB only captures the local properties of the AF peak, it does not work well when the SNR is low. An alternative approach for low SNR is based on the AF resolution cell [153–155]. This is an area in the delay-Doppler plane enclosed by a contour of the transmitted waveform AF within which a specified probability of detection is guaranteed for a given probability of false alarm and SNR value. Other approaches to waveform design for tracking include the use of polarization diversity to improve the tracking accuracy in the presence of clutter [156].

E.2. Waveform-Agile Sensing in MIMO Radar

Emerging MIMO radar techniques are increasing in popularity as they can expand the degrees of freedom in radar operation provided by their classical phased-array radar or multistatic radar counterparts, leading to improved system performance. Waveform-agile sensing is one of the core techniques in MIMO radar systems as their increased detection and estimation performance over conventional radar is due to the fact that MIMO radar can exploit spatial waveform diversity or superior beamforming performance by transmitting multiple different waveforms. When the transmission antennas and/or receiver antennas are widely-separated, space-diversity can be obtained [157–161] due to multiple, spatially distributed transmitters and receivers. On the other hand, if the antennas are colocated, diversity and beamforming can be achieved by designing a different waveform for each antenna [29, 30, 162–168]. Various studies have been recently published that compute the CRLB, under certain assumptions, when estimating target parameters[29, 30, 157, 160, 164, 169]. Also, the MIMO radar AF and its relation to the CRLB were discussed in [170, 171].

Waveform design for MIMO radar was investigated in [29–35]. Specifically, in [29, 30], waveform optimization was used to estimate parameters of stationary multiple targets in spatially colored interference and noise. In [31], waveform design was used to minimize the MSE when estimating angles-of-arrival, whereas in [32], the authors designed optimized space-time codes to achieve maximum diversity in the presence of correlated clutter. By controlling the space-time (or azimuth-frequency) distribution of the transmitted signal, and with knowledge of the clutter and/or target statistics, it was shown in [33] that it is possible to achieve significant improvements

in detection performance. In [143], the transmitted waveforms were designed using an information theoretic approach. In [34], radar waveforms were optimized using prior information on the extended target and clutter, whereas in [35], the waveform was designed so that the collocated MIMO radar could achieve frequency diversity and avoid SNR loss.

The transmission waveform for each MIMO radar sensor was designed using the CRLB approach under a high SNR assumption and a total power constraint in [36, 37]. In [36], an agile sensing algorithm was proposed to optimally select the transmission waveform of collocated MIMO sensors in order to improve target localization. The CRLB for the joint estimation of the reflection coefficients and the range and direction-of-arrival of a stationary target were derived, according to which the configured waveform parameters were determined to minimize the trace of the predicted error covariance by assuming that the covariance of the observation noise could be approximated by the CRLB for high SNR. The duration and phase function parameters of generalized frequency-modulated chirps were chosen to minimize the estimation MSE under constraints of fixed transmission energy and constant time-bandwidth product. In [37], waveform-agile sensing for dynamic target tracking was investigated for widely-separated MIMO radars. The CRLB derived in [169] was used to predict the tracker performance for waveforms with varying parameters that were determined to minimize the trace of the predicted tracking error covariance matrix. The improved tracking performance in the estimated target position when the waveforms were optimally configured is shown in Figure 13(a); the figure compares the tracking MSE for MIMO radar systems with and without waveform agility. Similar improvements were also observed for estimating the target velocity. Figure 13(b) shows the optimally-selected waveform duration at each time step.

E.3. Agile Sensing in Underwater Environments

As underwater acoustic environments can cause many distortions, such as multipath and time-dependent dispersive frequency shifts, waveform agility has the potential of improving underwater acoustic signal processing. For example, following existing underwater environment models such as the normal-mode models [172, 173], transmission waveforms can be adapted to match propagation characteristics in active sensing systems. In another example, observation waveform parameters can be selected to optimize the performance of passive acoustic localization systems.
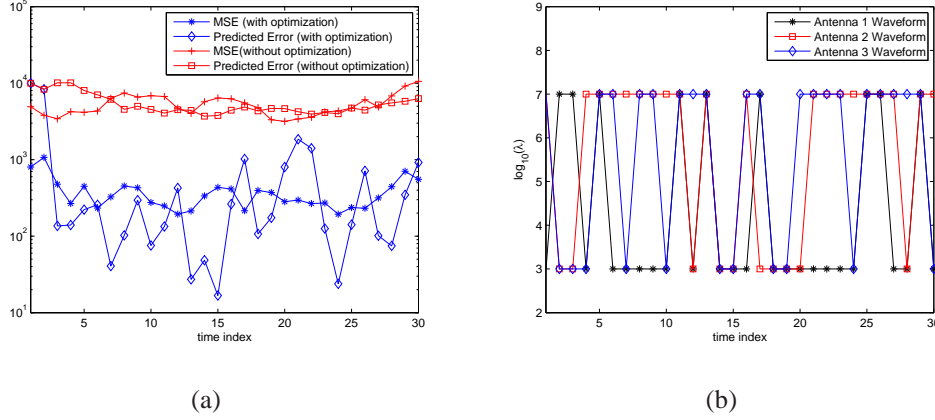
Figure 13: (a) Tracking MSE and predicted error for the x-Cartesian coordinate of the position of the target. (b) Optimally-selected waveform duration at each time step.

E.3.1. Receiver Waveform Design in Shallow Water Environments

Phase-coherent systems have been considered for underwater communications as they can adaptively track the time and frequency spread of the channel and can correct intersymbol interference, leading to higher data rates [174–177]. Space-time techniques [178–181] and time-reversal (or phase-conjugated) techniques [182–187] can also be used to obtain diversity in shallow water environments. In [188], a characterization of the shallow water environment was considered using a time-frequency (TF) approach that matches the dispersive transformation on the transmitted waveform. This characterization was successfully used for shallow water communications to obtain time-dispersion diversity matched to waveforms with very high bandwidth.

A receiver waveform design approach for dispersive systems was investigated in [189–193]. Specifically, a general waveform characterization based on the normal-mode model was developed for shallow water environments based on a frequency domain formulation. This assumes perfect waveguide conditions and thus consists of a homogeneous fluid layer with a soft top and rigid bottom. This environment characterization describes a linear time-varying (LTV) dispersive system which can cause different frequencies to be shifted in time by different amounts [188, 194]. Waveform design and diversity approaches were used to exploit the potential diversity embedded in the model when the receiver was appropriately designed to match the dispersive changes. A blind method was developed for separating the TF dispersive components of the received waveform. The blind separation method first identified the TF structure of the received signal components,
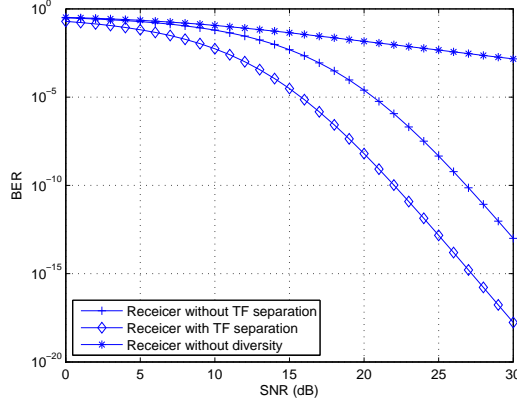
Figure 14: BER and diversity performance for different receivers when time-frequency mode separation was used.

and then it separated the components using a TF-based nonunitary warping technique. After the separation of each mode component, a pilot-aided communication receiver was used with an appropriately designed transmitted waveform and receiver structure to obtain time-dispersion diversity. Specifically, both the transmitter and receiver were designed to match the dispersive shallow water characteristics. The bit-error-rate (BER) simulation results are shown in Figure 14 for 0-30 dB SNR. The numerical results showed the BER and diversity order performances of three different types of receivers: with TF component separation, without TF component separation, and without diversity. The receiver without diversity used a single matched filter to receive the whole signal and hence did not achieve any diversity levels. The BER performance of the receiver with TF component separation outperformed the other two since it avoided interference between the normal modes.

E.3.2. *Parameter Selectivity in Underwater Tracking*

In underwater localization and tracking, matched-field processing uses acoustic propagation received waveform models, and it compares the output from a sensor array with the model outputs over a range of assumed source positions. The estimate of the source location is the best match between the measured and modeled array outputs. Following [195, 196], many source range and depth estimation techniques were developed using vertical array techniques based on normal-mode representations [197–203] or ray representations [204–212] of the received waveform. Matched-field tracking techniques incorporate the source motion as one of the parameters

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and include environmental source tracking [213], multivalued Bartlett processing [214], ambiguity surface averaging [215], optimum uncertain field tracking, and optimal minimum variance track-before-detect [216]. In [217, 218], the source motion model was assumed to be a uniformly moving target whose speed or direction did not change over the track duration. An initial investigation in applying sequential estimation to matched-field tracking was presented in [219].

For shallow underwater tracking, a parameter-agile sensing framework was used, together with a widely-used motion model for maneuvering targets and the sound field representation [38]. This framework assumed multiple passive acoustic sensors that were distributed at different locations in the water column to observe data in order to correctly track a target in a shallow water environment. A dynamic parameter-agile sensing algorithm was developed to minimize the predicted MSE of the target state's estimates in order to enhance the tracking algorithm performance. For tracking, the unscented Kalman filter and particle filter were used due to the highly-nonlinear relationship between the measurements and the states of the moving target. In this sensor network scenario with multiple mobile sensors and a data fusion center, a tracking algorithm was developed in which each sensor could schedule its own parameters to optimally obtain measurements, and the measurements were transmitted to the fusion center to estimate the target's location and velocity. A sequential quadratic programming algorithm was used to determine the sensor parameters in order to minimize the predicted MSE for estimating the target states. The tracking performance of a particle filter (PF) algorithm and a particle filter with sensor parameter selectivity (PF-PS) algorithm were compared using numerical simulations and demonstrated in Figures 15(a) and 15(b). Figure 15(a) shows the trajectory of the target and corresponding tracking results. Figure 16(a) shows the observation frequencies used by each sensor. As demonstrated, the tracking sensors selected different frequencies at each time. Figure 16(b) shows the trajectory of each sensor; the sensors tried to find the best observation position in order to minimize the predicted MSE. Figure 15(b) provides the averaged MSE. The results show that the best performance was obtained by the PF-PS algorithm as the sensors can predict the optimal observation position and frequency, resulting in improved tracking performance.

F. Conclusions

When trying to achieve the full adaptation of a sensing system, it is important to consider as many aspects as possible: from the wireless network capability of the system, to the information
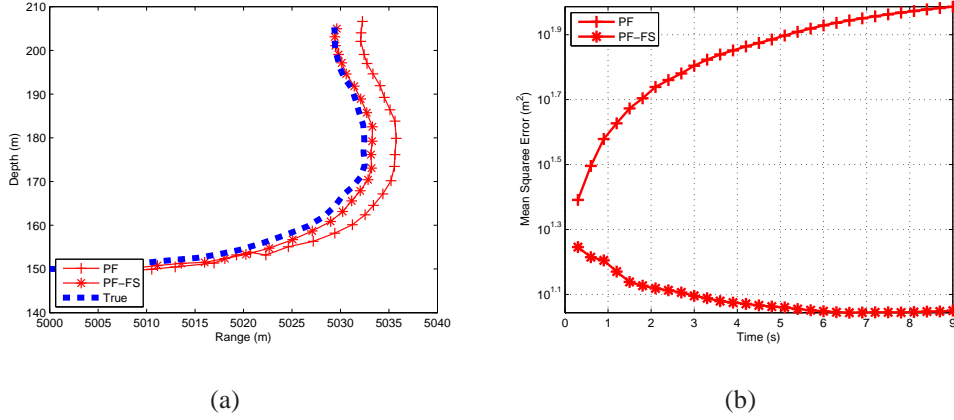
Figure 15: (a) Tracking performance of the particle filter (PF) and particle filter with parameter selectivity (PF-PS) for moving sensors. (b) MSE performance of two algorithms.

inference approaches from all the sensors in the network, to sensor system resource constrained computing, to optimal adaptive algorithms for dynamically adjusting sensor parameters and sensing strategies. This paper provided an overview of the latest advances in this area; an attempt was made to provide as many relevant references as possible (but, due to space constraints, we could not include all references on the topic). Applications were also discussed for sensor, signal and information processing. Some examples included: real-time wireless sensor networks for acoustic scene characterization, wireless sensor networks using distributed inference models and orthogonal fading channels, multiple-core processor implementation of particle filter estimation algorithms, adaptive waveform design algorithms in MIMO radar sensing, and parameter selectivity for underwater acoustic matched field tracking.
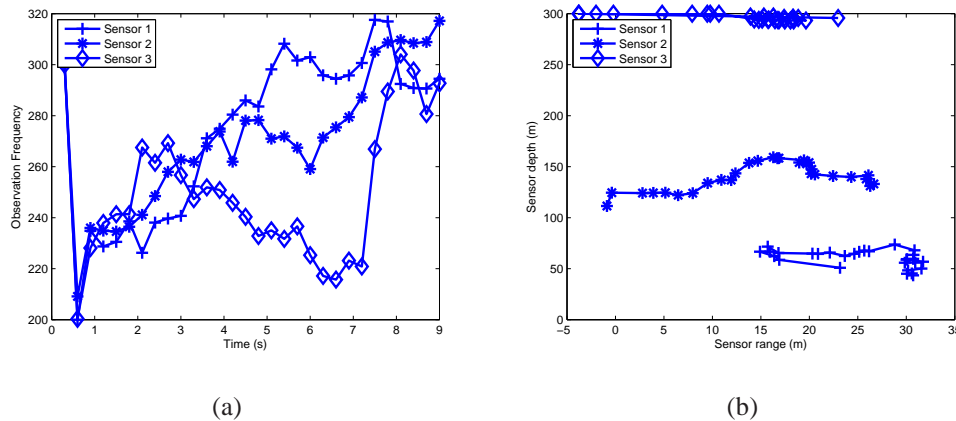
Acknowledgements

Figure 16: (a) Observation frequencies, and (b) observations positions of each sensor selected by the PF-PS algorithm.

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